A SELF-VALIDATING CONTROL SYSTEM BASED APPROACH TO PLANT FAULT DETECTION AND DIAGNOSIS

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ABSTRACT

An approach is proposed in which fault detection and diagnosis (FDD) tasks are distributed to separate FDD modules associated with each control system located throughout a plant. Intended specifically for those control systems that inherently eliminate steady state error, it is modular, steady state based, requires very little process specific information and therefore should be attractive to control systems implementers who seek economies of scale. The approach is applicable to virtually all types of process plant, whether they are open loop stable or not, have a type or class number of zero or not and so on. Based on qualitative reasoning, the approach is founded on the application of control systems theory to single and cascade control systems with integral action. This results in the derivation of cause-effect knowledge and fault isolation procedures that take into account factors like interactions between control systems, and the availability of non-control-loop-based sensors.

1. INTRODUCTION

For the sake of both economy and safety, online process monitoring, fault detection and fault diagnosis have received significant attention in recent years. Becraft and Guo et al. (1991) have surveyed a number of methods pertaining to fault diagnosis and have pointed out that each method manages to capture or model some subset of the features of diagnostic reasoning about operating conditions, and thus may be more suitable than other techniques for a particular class of problem. Although a lot of approaches have since been developed, still none can be viewed as having general applicability. Heuristic methods are fast and do not require a plant model, but are comparatively brittle because they cannot handle situations that are not explicitly anticipated. Model-based techniques are less brittle, but pose other problems: most industrial chemical processes are unique, it is expensive to build high-fidelity first-principles models of these processes and very difficult to anticipate all the abnormal situations that might arise; neural network based methods require considerable data and long training times and might have difficulty in diagnosing novel faults.

The main motivation for the development of the method described here is to provide a distributed scheme, because virtually all the other methods take a centralised view in that design & analysis are normally carried out from the top, say from a plant schematic, and FDD tasks are implemented centrally on something like a DCS Supervisor. This appears to be contrary to current developments: to exploit economies of scale, "economic pressures are dispersing machine intelligence away from centralized computers toward distributed (Fieldbus) devices " (Clarke, 1995). If one looks at the measurements collected from a process plant, a large proportion relate to the control loops, the rest are largely collected to ensure that operation is within allowable constraints. Since the hardware modules associated with these control loops are distributed throughout the plant, it seems sensible to distribute associated detection & diagnosis tasks in a similar manner. The role of each of these detection & diagnosis modules would not be confined to the validation of the performance of the closed loops, each module would also monitor the performance of the process located in the proximity of these loops. The boundaries specified for individual module responsibilities are likely to overlap one another so their union should encompass the entire plant. Economies of scale would be achieved if minimal use could be made of mathematical models. This would facilitate common software that could be configured at the same time as individual loops were *tuned*. Clearly these economies of scale would be diminished if the algorithms were too plant specific and required knowledge not readily available from the plant.

Such a vision will not be realised easily. Considerable research and debate are required before practicable implementations evolve. The method described here is a contribution towards this goal. Its novelty lies in its focus on the control system and on how it responds, in the steady state, to faults and disturbances in both the control system and in the local plant. Thus the focus is on distribution. It has many limitations and issues of implementation have yet to be addressed. However it might be appropriate for many process plants particularly those under standard single or cascade PID control. Some of the limitations are as follows:

(1) the controllers themselves must perform to specification and all control loops must guarantee zero steady state error e.g. because they have integral action;
(2) the fault must remain until a new steady state is reached and that this change in steady state must be detected;
(3) multiple faults can only be diagnosed if they are separated either spatially, i.e. in different parts of the plant, or temporarily, i.e. a new steady state is arrived at before the next fault occurs;
(4) reasoning is performed qualitatively and hence no quantitative results are obtained;
(5) controller outputs, together with measurements of the control variables must be available as *observations*.

A likely communications architecture is shown in Figure 1. The detection & diagnosis modules are called SEVACS to highlight a possible relationship with SEVA components as described by Henry and Clarke (1993) and by Clarke (1995). Note that the approach has two components, a distributed component (SEVACS) and a central component (the FDD Supervisor). In the distributed component, candidate sets of faults and disturbances would be hypothesised by reasoning qualitatively about how steady state deviations, observed in the control system, might have been caused. This reasoning process is based on qualitative equations derived for that particular form of control system. In the central component, the candidate sets generated by the various SEVACS are then fused by applying various isolation procedures, all of which take into account known interactions between control systems and sign information output from the SEVACS.

It is envisioned that this approach would be implemented in two stages, as part of the (offline) design stage and then, online, during commissioning. At the offline stage the plant would be decomposed into manageable compartments and each control system would be considered in turn. The following characteristics would then be identified/hypothesised for each control system:

- its structure, i.e. whether it has a standard form like a single loop or double, cascade loops or whether a new special form has to be recognised;
- the process Type Number (Dorf and Bishop, 1995) (if known);
- open loop stability (if known);
- steady state gains between interacting loops (if known).

Based on these characteristics, an appropriate configuration would then be downloaded to each of the detection & diagnosis modules. During commissioning, online procedures would then be executed to obtain those items above that were still unknown. In addition the modules would be configured to detect changes in steady state and the FDD supervisor would be specified.

SEVACS Modules

In the approach proposed here fault isolation is achieved by reasoning about steady state deviations in measured variables by referring to cause-effect knowledge of individual control systems. Section 2 analyses how standard control systems respond to faults and disturbances, in general, by referring to linear control systems theory and to signed-directed-graph (SDG) representations. Both linear and weakly non-linear (i.e. linearisable) processes are considered. Section 3 describes the cause-effect knowledge that can be generated from this analysis, and which can be downloaded to the various modules. Issues of generality, in terms of the diversity of disturbances and non-linearities, are discussed in the Conclusions.

FDD Supervisor

It is envisioned that the SEVACS modules would output analyses every time the process obtained a new steady state. By applying a choice of reasoning processes that are based on a search & test strategy described in Sections 4 & 5, the Supervisor would then fuse these analyses to isolate the cause. The level of isolation depends on the knowledge available and SDGs can facilitate this. The procedure described in Section 4 is somewhat specific, a more general, but more complicated, procedure is offered in Section 5 as an alternative. The approach is demonstrated using a simple CSTR example in Section 6.

Steady State Change Detection

The approach depends on the availability of procedures to detect a change in steady state. Although this problem is not new (see for instance, Cao and Rhinehart, 1995, 1997; Theilliol et al., 1995), it is not clear whether steady state identifiers have been implemented successfully on a large scale plant. Albers (1997) has discussed the application of steady state identifiers to data reconciliation and error detection, whilst workers on real-time optimisers (see for instance, Pierucci et al., 1996) and PCA (see for instance, Vedam and Venkatasubramanian, 1999) do not comment on the issue. Figure 2b shows the kind of output that is sought: the temperature data of figure 2a has been converted into a time series of R-statistics (Cao and Rhinehart, 1995, 1997), which in turn has been analysed by applying a hypothesis test to detect if a change has occurred; this has then been automatically interpreted into the more meaningful form shown. The key to figure 2b is as follows: level 3 occurs when it is not possible to make a decision because of insufficient data at that time, level 2 arises when no-decision is available because the plant is not in a steady state, levels ±1 arise when a new steady state is deemed to have been obtained (the sign denotes the direction), level 0 is obtained when this new steady state is 'accepted' and the test procedure is reset. Thus the change in steady state, which can be observed in figure 2a, is detected about 1 hour later (figure 2b) and the deviation is negative in direction.

The steady state requirement is quite demanding. Fortunately this requirement can be loosened, at least in one aspect, that of long settling times, which have the potential to render the approach impracticable. An early decision on responses with long settling times can be made, provided asymptotic trajectories can be detected as such. Another issue is that of time delays. Being steady state based, the concept is independent of any time delays in the plant. However time delays are likely to make steady state change detection more difficult, increase the time before a new steady state can be identified and cause confusions, for instance if one part is deemed to be in steady state whilst another is not. Although important, these issues were outside the scope of the work described here.

Background

A considerable amount of literature has been published about fault detection and diagnosis. The focus here is on the two most relevant aspects: on distributing diagnostic tasks to control systems and on those non-distributed methods that might be viewed as having some similarities with the approach described here.

Little has been written about distributing diagnostic tasks presumably because traditionally, the diagnostic engineer's view of feedback control is that it complicates, rather than aids, diagnostic reasoning. Feedback control adds to the complexity of fault detection in process plants by masking measurement deviations that might indicate a fault, and by making it difficult to distinguish between a sensor, actuator, or plant failure (Henry and Clarke, 1993). Control systems offer little decision-making assistance to an operator during the occurrence of process faults or abnormal disturbances, and in many cases, the actions of the control system can mask manifestations of the fault that would aid the operator in determining the cause of the process fault (Wilcox and Himmelblau, 1994a, 1994b). A similar research activity is that of control loop performance monitoring (Harris, 1989; Desborough & Harris, 1992; Stenfelj et al., 1993; Tyler et al., 1996; Thornhill et al., 1999; Kesavan et al., 1997). This differs from that proposed here because it focuses solely on the control loop. Other researchers seek to partition FDD tasks as opposed to distribute them. See for instance, Finch & Kramer (1988) and Prasad et al (1998) who examine ways in which diagnostic knowledge can be structured for large scale process systems. It is difficult to see how 'distributed' versions of many techniques could be obtained: for instance multivariable statistical process control (MSPC), gross error detection and data reconciliation (Rollins and Davis, 1992; Crowe, 1996; MacGregor and Kourti, 1995; Tong and Crowe, 1995; Albuquerque & Biegler, 1996; Heyen et al., 1996;

Schraa and Crowe, 1996; Bagajewicz & Jiang, 1997; Bakshi, 1998; Dunia and Qin, 1998; Luo et al., 1998; Jiang et al., 1999; Martin and Morris et al., 1999; Nounou and Bakshi, 1999; Sanchez et al., 1999; Shao et al., 1999). An alternative avenue of research that might be worth pursuing is based on neural networks and wavelets (see for instance non-distributed approaches by Rengaswamy and Venkatasubramanian (1995), Vedam and Venkatasubramanian (1997), Chen et al. (1999) and Wang et al. (1999)).

Based on qualitative reasoning, the proposed approach has been developed, in part, by referring to SDG representations of control systems. Although the application of SDG-based reasoning to fault diagnosis is not new, previous work has focused on the process plant, with its associated control and sensory systems, as a single entity (e.g. Shiozaki et al., 1984; Tsuge et al., 1984a, 1984b; Kramer and Palowitch, 1987; Kutsuwa et al., 1988; Mo et al.,1997). Although not directly relevant because the approach cannot be distributed, it is interesting that Vedam and Venkatasubramanian (1999) have developed a hybrid approach based on PCA and SDG because PCA is a steady-state based approach. Wang et al. (1995) have applied fuzzy qualitative reasoning method to assess process plants whilst Lunze and Schiller (1999) have explored fault diagnosis based on qualitative and probabilistic logic models. Finally the reader is referred to Chantler et al. (1998), which is considered noteworthy because it outlines various implementations that have been examined in realistic situations.

Long-term Vision

Looking into the future Figure 3 summarises the overall procedure that might be applied if the approach was to be implemented on a large scale plant.

2. REPRESENTATIONAL ISSUES FOR SEVACS KNOWLEDGE GENERATION

This section examines various ways that cause-effect knowledge can be represented to facilitate its generation. The first step is to introduce nomenclature relating to block diagram representations of two standard control systems (Section 2.1). These block diagrams are then analysed in Section 2.2 to produce equations that can generate cause-effect knowledge. An alternative representation (based on SDGs) is then considered in Section 2.3.

2.1 Nomenclature

The various variables used are defined before going any further. A simple single loop control system is represented by the block diagram shown in Figure 4: all variables represent deviations, θ_r is the deviation in the set-point/reference variable, θ in the controlled variable, d_m in the sensor bias, d_v in the valve bias, d_p in the process disturbance and x in the controller output. Parameter K_c is the proportional gain of the controller and parameters K_v, K_p and K_d are respectively the valve, process and process disturbance steady state gains. $G_c(s)$, $G_v(s)$, $G_p(s)$ and $G_d(s)$ are transfer functions of the controller, valve, process and disturbance respectively. Note that this structure represents only one form of PID control. Although other ways of implementing standard three-term control, e.g. as PI-D or I-PD, would result in different structures, all would lead to the same results because the approach is steady state based. Variables that pertain to a cascade control system are defined in a similar way (Figure 5). The approach described here is based on an analysis of qualitative variables that assumes that the basic qualitative operations are as defined in Table 1: a qualitative variable [x] is merely defined as the sign of variable x (De Kleer & Brown, 1984; Forbus, 1984). In comparison with its normal or nominal value, [x] has four qualitative values: '+' means x deviates high; '–' means x deviates low; '0' means x has no change and '?' means the deviation of x cannot be decided.

In order to implement qualitative operations, another definition is required: {K} represents the sign of the gain K and can be viewed as an operator. Qualitative operator {K} only has two values: '+' when K>0 and '–' when K<0. The operation {K} is defined as follows:

$\{-K_1\}=-\{K_1\}$;

$\{+K_1\}=+\{K_1\}=\{K_1\}$;

$-\{-K_1\}=\{K_1\}$;

$\{K_1K_2\}=\{K_1\}\{K_2\}=\{K_2\}\{K_1\}$;

$\{K_1/K_2\}=\{K_1K_2\}$.

2.2 Generation Of SEVACS Inter-Node Relationships

This sub-section examines how faults and process disturbances can affect individual control systems, the results are then used to construct SDG representations in the next sub-section. Only the main ideas are given here, a more comprehensive explanation can be found in Chen (2000). The processes under control must first be categorised in two ways: open loop stable or not, has a Type Number of zero or not. The most common of these is considered here, Appendix 1 describes all the other cases.

2.2.1 Open loop stable processes with zero Type Number

Consider the PID control system block diagram shown in Figure 4 and assume that, when linearised

$$G_c(s) = K_c\left[1+\frac{1}{T_i s}+T_d s\right] \quad ; \; K_c\neq 0,\; T_i>0,\; T_d\geq 0\; ; \qquad (1)$$

$$G_v(s) = \frac{K_v}{T_v s+1} \quad ; \; K_v\neq 0,\; T_v\geq 0\; ; \qquad (2)$$

$$G_p(s) = \frac{B_m s^m + B_{m-1}s^{m-1}+\cdots+B_1 s+B_0}{s^n + A_{n-1}s^{n-1}+\cdots+A_1 s+A_0}\; ;$$

$$m, n\in Z,\; m\geq 0,\; n\geq 1,\; A_j>0\; (j=0,..,n-1),\; B_0\neq 0\; ; \qquad (3)$$

$$G_d(s) = \frac{D_d s^d + D_{d-1}s^{d-1}+\cdots+D_1 s+D_0}{s^n + A_{n-1}s^{n-1}+\cdots+A_1 s+A_0}\; ;$$

$$d, n\in Z,\; d\geq 0,\; n\geq 1,\; A_j>0\; (j=0,..,n-1),\; D_0\neq 0; \qquad (4)$$

Then

$$\theta(s)=\frac{K_cK_v(T_iT_ds^2+T_is+1)(B_ms^m+\cdots+B_1s+B_0)}{\Delta(s)}[\theta_r(s)-d_m(s)]$$
$$+\frac{T_is(T_vs+1)(B_ms^m+\cdots+B_1s+B_0)}{\Delta(s)}d_v(s)+\frac{T_is(T_vs+1)(D_ds^d+\cdots+D_1s+D_0)}{\Delta(s)}d_p(s)$$

(5)

and

$$x(s)=\frac{K_c(T_iT_ds^2+T_is+1)(T_vs+1)}{\Delta(s)}\{(s^n+A_{n-1}+\cdots+A_1s+A_0)[\theta_r(s)-d_m(s)]$$
$$-(B_ms^m+\cdots+B_1s+B_0)d_v(s)-(D_ds^d+\cdots+D_1s+D_0)d_p(s)\} \quad (6)$$

where,

$$\Delta(s)=T_is(T_vs+1)(s^n+A_{n-1}s^{n-1}+\cdots+A_1s+A_0)+K_cK_v(T_iT_ds^2+T_is+1)(B_ms^m+\cdots+B_1s+B_0) \quad (7)$$

In the steady state, and if the controller functions as expected,

$\theta=\theta_r-d_m$ (8)

$e=0$ (9)

$$x=\frac{A_0}{K_vB_0}\theta_r-\frac{A_0}{K_vB_0}d_m-\frac{1}{K_v}d_v-\frac{D_0}{K_vB_0}d_p \quad (10)$$

Qualitatively, we have:

$[\theta]=[\theta_r]-[d_m]$ (11)

and $[x]=\frac{\{A_0\}}{\{K_vB_0\}}[\theta_r]-\frac{\{A_0\}}{\{K_vB_0\}}[d_m]-\frac{[d_v]}{\{K_v\}}-\frac{\{D_0\}}{\{K_vB_0\}}[d_p]$, (12)

where $\frac{B_0}{A_0}$ can be viewed as the steady state gain K_p and $\frac{D_0}{A_0}$ can be viewed as the steady state gain K_d in Figure 4.

Similarly the cascade control system in Figure 5 can be analysed to obtain the following equations:

$$[x_1]=\frac{\{A_{01}\}}{\{B_{01}\}}[\theta_r]-\frac{\{A_{01}\}}{\{B_{01}\}}[d_{m1}]-\frac{\{D_{01}\}[d_{p1}]}{\{B_{01}\}}+[d_{m2}] \quad (13)$$

and

$$[x_2]=\frac{\{A_{01}A_{02}\}[\theta_r]}{\{B_{01}B_{02}K_v\}}-\frac{\{A_{02}D_{01}\}[d_{p1}]}{\{B_{01}B_{02}K_v\}}-\frac{\{A_{01}A_{02}\}[d_{m1}]}{\{B_{01}B_{02}K_v\}}-\frac{\{D_{02}\}[d_{p2}]}{\{B_{02}K_v\}}-\frac{[d_v]}{\{K_v\}}, \quad (14)$$

where subscripts containing a 1 pertain to the outer loop controller and those with a 2 pertain to the inner loop, $\frac{B_{01}}{A_{01}}$ can be viewed as the steady state gain K_{p1}, $\frac{B_{02}}{A_{02}}$ can be viewed as the steady state gain K_{p2} , $\frac{D_{01}}{A_{01}}$ can be viewed as the steady state gain K_{d1}, and $\frac{D_{02}}{A_{02}}$ can be viewed as the steady state gain K_{d2}.

2.2.2 Analysis Of Inter-Node Relationships

The focus here is on the single loop. A similar approach can be taken for the cascade case. If the Routh-Hurwitz Criterion were to be applied to the closed loop equations, then one of the necessary conditions for closed loop stability would be $K_c K_v B_0 > 0$.

If the process has an odd number of open loop unstable poles, then $A_0<0$, so that $\{A_0\}=-$ and $[\theta_r]$ or $[d_m]$ can cause [x] to take the opposite direction compared to a stable process where $A_0>0$; if the process has an even number of open loop unstable poles, then $A_0>0$ and $\{A_0\}=+$, $[\theta_r]$ or $[d_m]$ has the same effect on [x] compared to the stable process. In both cases, and for both stable and unstable processes, deviations in $[d_v]$ or $[d_p]$ will have the same effect on [x].

The directions of the deviations in the various observations can provide additional information with which to infer the 'direction' of the various fault hypotheses e.g. "fails-high" or "fails-low". If the process has a pure integrator, [x] will depend on deviations $[d_v]$ and $[d_p]$ and deviations in $[\theta_r]$ and $[d_m]$ are irrelevant.

2.3 Representing Control Systems By SDGs

An SDG can be viewed as an ordered pair, (*G, s*). Directed graph *G* can be represented as an ordered quadruple (*N, B, i, t*) consisting a set of nodes N, a set of branches *B*, and two incidence functions *i* and *t* which map the branches to their initial and terminal nodes, respectively. The second component of the pair (*G, s*) is a function which maps the branches of *B* to the set {+, –}. The state of a system is described qualitatively by a pattern *p* which is a function from the nodes of the graph to the set {+, 0, –}. A node mapping to qualitative value +, 0 or – indicates that the corresponding process variable is *high*, *normal* or *low* respectively.

An example of a SDG representation is shown in Figure 6. Here nodes D, E or F can be mapped to deviations $\underline{D_D}$, $\underline{D_E}$ and $\underline{D_F}$, all of which can take qualitative values +, 0 or – to indicate that the corresponding process variable is *high*, *normal* or *low* respectively.

In Figure 6, the circles around nodes D and E indicate that these nodes are measured; hence node F, which is not circled, is unmeasured. In this paper, ancestors of a node refer to those nodes that can cause this node to change or deviate. Descendants of a node refer to those nodes that can be caused to change or deviate because this node deviates. For example, in Figure 6, node D can be viewed as an ancestor of node E and node E can be viewed as a descendant of node D. Also note that each element of set B can be defined as a relation between an initial (or an ancestor) node to a terminal (or a descendant) node, e.g. b_1 is also a relation R_{DE} between node D and node E, and so on. Further background to SDG representations is given in Appendix 2.

Signed-directed-graph representations of control systems can be formed according to the equations and qualitative information given in the last sub-section. Figure 7(A) shows an SDG representation of a typical single loop control system, in which C, V, X and M represent the controller output, the valve opening, the controlled variable and the sensor measurement respectively; θ_r, d_v, d_p, d_m represent deviations in set-point, valve bias, process disturbance and sensor bias respectively. Signs of the branches in the SDG are determined from the relevant equations.

It is important to note that only d_p and node X interact with nodes or variables in other parts of the plant. To indicate this, the circled parts in Figure 7(A) can be lumped together and the figure can be simplified to Figure 7(B): θ_r and C are lumped into C node, d_v and V are lumped into V node, M and X are lumped into S node, and d_p is replaced by E, which is generalised to include exogenous disturbances and other process variables. Individual elements should still be treated separately when performing fault diagnosis. The whole control system can be viewed as a super-node that consists of several nodes that form a circle. This super-node can be analysed using control system related cause-effect knowledge that will be discussed in the next section.

A standard cascade control system can be treated in a similar way. Figure 8 shows a cascade control system where C1, C2, V, S2 and S1 represent the output of the outer loop controller, the output of the inner loop controller, the valve opening, the inner loop sensor node and the outer loop sensor node respectively. Nodes E1 and E2 represent outer loop process disturbances and inner loop process disturbances respectively. The entire cascade control system can be viewed as a super-node in which individual elements are treated separately when performing fault diagnosis. Only nodes S1 and S2 of the super-node can interact with other nodes or variables in the plant.

It is worth pointing out that, as has been discussed, for stability the sign product of any of the control loops in the above SDGs must be '−'.

3. SEVACS CAUSE-EFFECT KNOWLEDGE

Results from the previous section can now be applied to generate tables of cause-effect knowledge, which can be downloaded to the SEVACS. The contents of the tables differ depending on whether or not the process has a Type Number of zero. Here the focus is on controlled processes with a Type Number of zero, the other case is given in Appendix 3. Equations (8) — (14) were referred to extensively when deriving this knowledge. Tables 2 and 3 describe the various effects that individual faults would have on the observations available for single loop and cascade loop control systems respectively. Faults like a dead sensor, or a sticking valve or a large process disturbance are not considered because, in these circumstances the steady state is unlikely to be obtained. These faults would be addressed by using other approaches. The following sub-sections discuss how the signs of the fault or disturbance (e.g. high or low) would be determined.

A sensor bias in a single loop control system or in the outer loop of a cascade control system. If the sensor biases, the controller will take action to compensate for this with the net effect that there will be a deviation in the controller output and the sensor measurement will return to its normal value. The direction of the sensor bias can then be determined by looking at the following (Figure 9):

- *Rsc*: the relation between the sensor measurement and the controller output;
- <u>*Dc*</u>: the steady state deviation of the controller output.

The various possibilities are listed in the decision table in Figure 9.

A sensor bias in the inner loop of a cascade control system. Both the inner and the outer loop controllers will attempt to compensate (Figure 10) with the net effect that the sensor deviation observed (<u>*Ds*</u>) will have the same direction as the (inner) sensor bias. The decision table in the Figure 10 summarises this.

An exogenous/ancestor fault or disturbance. In both single and cascade loop cases, such occurrences will be compensated by the controllers with the net effect that there will be a deviation in the controller outputs. The direction of the exogenous/ancestor fault or disturbance can then be determined by looking at the following:

- *R**: the relation between a sensor measurement and a controller output;
- *Rex*: the relation between an exogenous variable and a sensor measurement;
- <u>*D**</u>: the steady state deviation in a controller output.

Although these 3 factors refer to the various loops differently (see Figure 11) the various outcomes can be represented in a single decision table as shown.

A Valve bias. If the valve biases, there will be a deviation in the controller output with the effect that the sensor measurement will return to its normal value. The direction of the valve bias can then be determined by looking at the following factors (Figure 12):

- *Rcv*: the relation between the controller output and the valve opening;
- <u>*Dc*</u>: the steady state deviation in the controller output.

The possible outcomes are as shown in the table in Figure 12.

4. FAULT ISOLATION

It is very easy to isolate faults like a dead sensor or a large exogenous fault/disturbance or a sticking valve, by applying appropriate simple heuristic rules. It is more difficult to isolate faults like a sensor bias, or a small exogenous fault/disturbance. In these circumstances, the controlled variable, and its effect on descendants, is arguably the key to fault isolation: *with a sensor bias, the controlled variable will deviate from its nominal value and descendants of the controlled variable will be affected; with a valve bias, or with an exogenous fault/disturbance, the controlled variable will remain at its nominal value and its descendants will not be affected*. This fault isolation principle leads to a search and test strategy composed of two alternative strategies, the choice between them depending on whether or not any two measured (i.e. circled) nodes interact bi-directionally and on whether or not these relationships are actually 'invoked' when a particular fault arises. This can be programmed as a combination of operations on sets and on if-then-else rules.

4.1 Control Systems with Uni-directional Interactions

A simple set of rules can be derived for those control systems with uni-directional interactions that have the fairly general feature shown in Figure 13. Of importance here are the relationships between a controlled variable and its neighbouring measured nodes: S1 is a controlled variable, S2 is a measured descendant of S1 (it could be another controlled variable), E1 is an ancestor of both S1 and S2 (as their process disturbance), it affects S1 and S2 simultaneously, E2 is an ancestor of S1 and only affects S1. Thus S1-sensor-bias should be viewed as a process disturbance to S2, the descendant of S1.

If S1 pertains to a Type Number 0 controlled process and its control loop deviates (any element in the control loop deviates), then, initially, the fault candidate will be {S1-sensor-bias, E1, E2, valve-bias in the S1 control loop}. There are now two possibilities:

- S2 is affected: because E1 is the common ancestor of S1 and S2 and according to the fault isolation principle, the fault candidate set shrinks to {S1-sensor-bias, E1}; if the direction of the deviation of S2 contradicts that expected from the S1-sensor-bias, {E1} is the only fault route.
- S2 is not affected: the fault candidate set shrinks to {E2, valve-bias in the S1 control loop}. If there is no more information about E2, then these two possibilities can not be separated. Otherwise, if E2's descendants deviate, E2 will be the only fault route.

It should be noted that when S2 is in another control loop, if that controller deviates, S2 should be viewed as being affected, though the sensor measurement of S2 itself doesn't deviate.

If S1 is pertaining to a Type Number > 0 controlled process instead then, although S1-sensor-bias doesn't cause the S1 control system to deviate, it causes S1 descendants to deviate. Therefore in this case, only the valve-bias in the S1 control loop and the S1 process disturbances such as E1 and E2 can cause S1 control loop to deviate, S1-sensor-bias cannot be deduced from the deviation of any element in the S1 control loop but from the deviation of S2, the S1 descendant.

4.2 Control Systems with Bi-directional Interactions

Here the controlled variables S1 and S2 affect each other (Figure 14); either can pertain to a single loop (s.l.) control system or to the inner loop (i.l.) or to the outer loop (o.l.) of a cascade control system. Then three different types of interactions must be considered: Type A interaction occurs when a controlled variable deviation in either a s.l. or o.l. affects the steady state performance of another s.l. or o.l. or vice versa. Similarly Type B interaction occurs when there is a bi-directional interaction between two control systems with one, and only one, of the inner loops affected. Type C interaction occurs when both inner loops are affected (i.e. not the outer loops). Note that the treatment of single and outer loops is the same because, in the latter, the non-interacting inner loop can be viewed as a virtual valve node. This can be seen in Figure 15 where V2′ is a virtual valve node.

4.2.1 Type A Interaction: Solely Single/Outer Loops Interact

Referring to Figure 15, S1 is one controlled variable that is controlled by the controller C1 and manipulated by the valve/actuator V1; S21 is the other controlled variable that interacts with S1, here S21 is controlled by a cascade control system that includes an outer loop controller C21 and an inner loop controller C22, S22 is as the inner loop controlled variable, V2 is as the manipulated valve/actuator. Nodes C22, S22 and V2 can be lumped together as a super-node V2′ (as a virtual valve node) so that this cascade control system can be viewed or analysed as a single loop control system. R_{S1S21} and R_{S21S1} represent the relations (or interactions) between the two controlled variables S1 and S21.

First consider the case that all the controlled processes belong to Type Number 0 processes. If only one of the control systems deviates, then the fault is local to that control system so the fault can be isolated using the method above; if both the control systems deviate, there are two possibilities:

- if S1 and S21 have at least one common ancestor, the fault candidate set is {S1-sensor-bias, S21-sensor-bias, one of the common ancestors' faults};
- if S1 and S21 have no common ancestor, the fault candidate set is {S1-sensor-bias, S21-sensor-bias}.

If signs of $\{R_{S1S21}\}$ and $\{R_{S21S1}\}$ are opposite, S1-sensor-bias and S2-sensor-bias can now be separated by the knowledge related to the two control systems, as shown in Table 4; otherwise they cannot be separated without further information. Referring to Figure 7(B), Table 4 has been derived by modifying and subsequently analysing Equation (12) for each controller: just simply replacing its [d_p] term with a compound disturbance term that consists of the effect of the sensor bias in the other control system (Chen, 2000).

If either or both the S1 controlled process and the S21 controlled process are capacitive, both sensor biases above cannot cause both control systems to deviate. However one sensor bias can be viewed as a process disturbance to the other controlled process and cause the respective control system to deviate; if both controlled systems deviate, there must be at least one common ancestor, which is the fault.

4.2.2 Type B Interaction: The Inner Loop of Only One of The Control Systems Interacts

For Type B interaction, a single control loop or the outer loop of a cascade control system interacts with an inner loop of a cascade control system. For example, in Figure 16, S1 is a single loop controlled variable that is controlled by controller C1 and manipulated by valve/actuator V1. Node S1 interacts with S22, where S22 is the inner loop controlled variable in a cascade control system in which C21 is the outer loop controller, C22 is the inner loop controller, S21 is the outer loop controlled variable and V2 represents the valve/actuator of the control system. R_{S1S22} and R_{S22S1} represent the relations (or interactions) between the two controlled variables S1 and S22. Node E2 represents the process disturbance to S21.

For convenience, suppose there is no common ancestor between the two control systems. Here a sensor bias on S1 can be viewed as an external disturbance/fault to the inner loop of the cascade control system, but an inner loop sensor bias on S22 has no effect on the single control system in the steady state. An external disturbance/fault to the outer loop of the cascade control system, say E2 in Figure 16, or a sensor bias on S21 can cause the single loop control system to deviate.

So, S1-sensor-bias, S22-sensor-bias, E2 or S21-sensor-bias can be isolated no matter what the relations between S1 and S22 are. For example, suppose all controlled processes here are not capacitive, if only C21 deviates, S22-sensor-bias is the fault; if only C1 and C22 deviate, S1-sensor-bias is the fault; if C1, C21, C22 deviate, E2 or S21-sensor-bias is the fault. The fault directions can be inferred from the cause-effect knowledge described previously.

It is worth pointing out that the knowledge or rules above will be different if some of the controlled processes are capacitive. However faults can still be isolated: if the S1 controlled process is capacitive, S1-sensor-bias will not cause C1 to deviate but it can affect the cascade control system and only cause C22 to deviate; if the inner loop controlled process is capacitive, C22 cannot be affected by E2 or S21-sensor-bias; if the outer loop controlled process is capacitive, C1 cannot be affected by S21-sensor-bias.

4.2.3 Type C Interaction: Inner Loops of Both Cascade Control Systems Interact

A Type C interaction is shown in Figure 17: one inner loop controlled variable S12 interacts with the other inner loop controlled variable S22. Node S12 is the inner loop controlled variable in a cascade control system in which C11 is the outer loop controller, C12 is the inner loop controller, S11 is the outer loop controlled variable and V1 represents the valve/actuator of the control system. Node S22 is the inner loop controlled variable in the other cascade control system in which C21 is the outer loop controller, C22 is the inner loop controller, S21 is the outer loop controlled variable and V2 represents the valve/actuator of the control system. R_{S12S22} and R_{S22S12} represent the relations (or interactions) between the two controlled variables S12 and S22. Node E1 represents the process disturbance to S11 and E2 represents the process disturbance to S21.

Again, for convenience, suppose there is no common ancestor between the two control systems. The inner loop sensor bias of one cascade control system will not affect the other cascade control system in the steady state. First consider the situation in which the controlled processes here are not capacitive. If only C11 deviates, S12-sensor-bias is a possible fault; if only C21 deviates, S22-sensor-bias is a possible fault. An outer loop process disturbance or outer loop sensor bias of one cascade control system can cause the other system to deviate, in which case the fault can be isolated using the following: if C11, C12 and C22 deviate, S11-sensor-bias or E1 is a possible fault; if C21, C22 and C12 deviate, S21-sensor-bias or E2 is a possible fault. Once again, the above faults directions can be inferred from the cause-effect knowledge.

The knowledge or rules above will be also different if some of the controlled processes are capacitive: if the S12 inner loop controlled process is capacitive, C12 cannot be affected by E1 or S11-sensor-bias; if the S11 outer loop controlled process is capacitive, C22 cannot be affected by S11-sensor-bias; if the S22 inner loop controlled process is capacitive, C22 cannot be affected by E2 or S21-sensor-bias; if the S21 outer loop controlled process is capacitive, C12 cannot be affected by S21-sensor-bias.

5. AN ALTERNATIVE FAULT ISOLATION METHOD FOR INTERACTING CONTROL SYSTEMS

The procedures described in the last section require different knowledge or rules for different processes. This section describes an alternative approach that is easier to realise as an auto-reasoning algorithm in a real-time fault diagnosis system. It does not rely on a large number of rules. The approach is to modify the SDG representation of interacting control systems by breaking the interaction between two control systems, and then to use the knowledge relating to the single or cascade control systems to isolate the faults. Thus the effect of one control system on the other is viewed as a process disturbance to that control system. Having modified the relevant SDGs, the fault isolation procedures of Section 4 can now be applied to individual controllers as before. Having isolated a fault, and if this fault is identified by more than one controller, then this fault hypothesis would be accepted provided that associated signs do not contradict. The rest of this section examines each type of interaction in turn.

- The SDG of two control systems with Type A interaction in Figure 15 can be modified as shown in Figure 18. The sensor biases (i.e. S1 bias and S21 bias) are represented by special process disturbances. Then $\{R^*_{S1S1}\}$ and $\{R^*_{S21S21}\}$ are always + unless the process pertaining to S1 or S21 is capacitive; if the process pertaining to S1 is capacitive , the link R^*_{S1S1} simply doesn't exist; if the process pertaining to S21 is capacitive, the link R^*_{S21S21} doesn't exist. R^*_{S1S21} and R^*_{S21S1} depend on the relation between S1 and S21. For example if S1 sensor biases high, then the respective controlled variable will be controlled at a value less than its nominal value and controlled variable S2 will see this effect as a negative going disturbance. It follows that, if the relations between S1 and S21 are as shown in Figure 15, then $\{R^*_{S1S21}\} = -\{R_{S1S21}\}$ and $\{R^*_{S21S1}\}= -\{R_{S21S1}\}$.

- The SDG of two control systems with Type B interaction in Figure 16 can be modified as shown in Figure 19. Again the sensor biases (i.e. S1 bias and S21 bias) are represented by special process disturbances. Variable E2 is represented as an exogenous disturbance to both S1 and S21 because, although E2 affects S21 directly, it affects S1 indirectly via C22 and S22. Suppose the relation between S1 and S22 is as shown in Figure 17 so that $\{R_{S1S22}\}$, $\{R_{S22S1}\}$, $\{R_{E2S21}\}$, $\{R_{S22S21}\}$ are known, then $\{R^*_{S21S1}\}$, $\{R^*_{S21S21}\}$, $\{R^*_{E2S1}\}$, $\{R^*_{S1S1}\}$, $\{R^*_{S1S22}\}$ can be determined by the following:

$$\{R^*_{S21S1}\} = \begin{cases} -\{R_{S22S1}\}\cdot\{R_{S22S21}\} & \text{; The process pertaining to S21 is not a capacitive process;} \\ not\ exist & \text{; The process pertaining to S21 is a capacitive process.} \end{cases}$$

$$\{R^*_{S21S21}\} = \begin{cases} + & \text{; The process pertaining to S21 is not a capacitive process;} \\ not\ exist & \text{; The process pertaining to S21 is a capacitive process.} \end{cases}$$

$$\{R^*_{E2S1}\} = -\{R_{S22S1}\}\cdot\{R_{E2S21}\}\cdot\{R_{S22S21}\}$$

$$\{R^*_{S1S1}\} = \begin{cases} + & \text{; The process pertaining to S1 is not a capacitive process;} \\ not\ exist & \text{; The process pertaining to S1 is a capacitive process.} \end{cases}$$

$$\{R^*_{S1S22}\} = -\{R_{S1S22}\}$$

- The SDG of two control systems with Type C interaction in Figure 17 can be modified as shown in Figure 20. Again the sensor biases (i.e. S1 bias and S21 bias) are represented by special process disturbances. Variable E1 is represented as an exogenous disturbance to both S11 and S22 because, although E1 affects S11 directly, it affects S22 indirectly via C12 and S12. Similar relationships can be constructed for E2. Suppose the relation between S12 and S22 is as shown in Figure 17 so that $\{R_{S12S22}\}$, $\{R_{S22S12}\}$, $\{R_{E1S11}\}$, $\{R_{E2S21}\}$, $\{R_{S12S11}\}$, $\{R_{S22S21}\}$ are known, then $\{R^*_{S11S11}\}$, $\{R^*_{S11S22}\}$, $\{R^*_{E1S22}\}$, $\{R^*_{E2S12}\}$, $\{R^*_{S21S12}\}$, $\{R^*_{S21S21}\}$ can be determined by the following:

$$\{R^*_{S11S11}\} = \begin{cases} + & \text{; The process pertaining to S11 is not a capacitive process;} \\ not\ \ exist & \text{; The process pertaining to S11 is a capacitive process.} \end{cases}$$

$$\{R^*_{S11S22}\} = \begin{cases} -\{R_{S12S22}\}\cdot\{R_{S12S11}\} & \text{; The process pertaining to S11 is not a capacitive process;} \\ not\ \ exist & \text{; The process pertaining to S11 is a capacitive process.} \end{cases}$$

$$\{R^*_{E1S22}\} = -\{R_{S12S22}\}\cdot\{R_{E1S11}\}\cdot\{R_{S12S11}\}$$

$$\{R^*_{E2S12}\} = -\{R_{S22S12}\}\cdot\{R_{E2S21}\}\cdot\{R_{S22S21}\}$$

$$\{R^*_{S21S12}\} = \begin{cases} -\{R_{S22S12}\}\cdot\{R_{S22S21}\} & \text{; The process pertaining to S21 is not a capacitive process;} \\ not\ \ exist & \text{; The process pertaining to S21 is a capacitive process.} \end{cases}$$

$$\{R^*_{S21S21}\} = \begin{cases} + & \text{; The process pertaining to S21 is not a capacitive process;} \\ not\ \ exist & \text{; The process pertaining to S21 is a capacitive process.} \end{cases}$$

6 A CSTR EXAMPLE

The CSTR process is shown in Figure 21: there are two outlets, the flow rate, F_1, is manipulated to regulate level, L, whilst a nominally constant flow rate, F, is drawn for a separate purpose; the reactor temperature, T, is maintained by varying the flow rate, FJ, through a heat exchanger installed in the CSTR and, in addition, concentration C_A is measured. Its design is somewhat contrived to enable bi-directional interaction between two of the control systems. A detailed description, including nomenclature is given in Appendix 4.

Although model equations can be derived for the hypothetical CSTR relatively easily, it might be difficult to justify the time and expense of developing detailed models for a large process plant. Thus, to reflect our desire for generality, the approach here ignores the existence of detailed mathematical models. Referring to the Introduction the following information needs to be obtained:

- the structure: it can be seen from Figure 21 that the CSTR has three control systems, one of which is cascade;

- the process Type Number and steady state gains: this minimum knowledge can either be obtained from a very simple mathematical model or from a process step test;
- open loop stability: from step tests.

Details of step test procedures can be found in Chen (2000). A simple SDG representation can be constructed, which is based on the above information. Figure 22 shows the SDG for the stable CSTR. Clearly if knowledge does exist then it would be a nonsense not to refer to it since greater fault isolation resolution would be obtained. In fact one can envisage a situation where, although a plant is commissioned with minimal knowledge, further knowledge is obtained with operational experience. Figure 23 shows a detailed SDG representation to reflect this increase in knowledge. This SDG has been constructed from steady state balances derived from the equations given in the Appendix 4. Note that there are three control systems (enclosed by dashed lines), two of which have single loops, the other has a cascade arrangement. Controller gains can either be forward or reverse acting (see Tables A.3 & A.4). When examining the unstable case, a number of changes have to be made because all the signs of the branches that take node T as their terminal node have to be inverted. It is assumed that the output from each circled node can be recorded either because it can be measured, as is usually the case for sensors, or because it has been calculated, as in the case of a digital control output. A list of faults considered is given in Table 5 together with their consequent deviations in the various measurements that can be recorded. These were obtained from a simulation constructed on the basis of the equations given in Appendix 4.

Fault 1: L-sensor-bias-high. If L sensor biases, then in the steady state all control systems will deviate. From Figure 22, both the level and the flow rate control systems have single loops and the interaction between L and F is of Type A. Initially the fault candidate set is {L-sensor-bias, F-sensor-bias, high-C_A, an unknown disturbance of L and F}. In addition the effects between L and F are opposite (Table 5) so that F-sensor-bias should be rejected and L-sensor-bias-high has been deduced. Note that the other two elements still remain. L-sensor-bias-high can then be further confirmed or inferred from the relation between the level and temperature control systems and then high-C_A and the unknown disturbance should be also common disturbances of F, L and T. Now consider the case where additional knowledge is available e.g. in the form of Figure 23: note first that a common disturbance to F, L and T doesn't exist and hence L-sensor-bias-high is the only fault that can be diagnosed. The fault can be also isolated using the alternative fault isolation method by constructing the simple, modified Type A SDG shown in Figure 24. Here L-sensor-bias and F-sensor-bias can both be viewed as process disturbances to L and F. The LC deviation (-) implies that the fault candidate set could be {L-sensor-bias-high, F-sensor-bias-high} whilst the FC deviation (-) implies that the fault candidate set could be {L-sensor-bias-high, F-sensor-bias-low}. So L-sensor-bias-high is the only possible fault that matches both possibilities.

Fault 2: T-sensor-bias-high. If T sensor biases, then in the steady state both the outer loop and the inner loop controllers of the temperature cascade control system will deviate. However neither the level control system nor the flow rate control system will be affected although concentration C_A will also deviate. It is worth noting that, if the temperature is open loop unstable, then the controller deviations will be opposite to those of the stable case. From Figure 22 and according to the cascade control loop deviations in Table 9, initially the fault candidate set could be {T-sensor-bias-high, high-C_A, an unknown common disturbance of T and C_A}. If further information is known (Figure 23), then although variable F_0 is a common disturbance of C_A and T, it can be removed from the candidate set because L controller doesn't deviate so neither does its ancestor F_0. An high-C_{A0}, low-K_0 or T-sensor-bias-high can all cause C_A to deviate high,. Low-K_0 and T-sensor-bias-high are not distinguishable from the SDG. Variable C_{A0} can only be eliminated if it meets the latter of the following two alternative conditions.

- If the temperature process is open loop stable or has an even number of open loop unstable poles, then the high-C_{A0} will cause the same deviations as T-sensor-bias-high so the high-C_{A0} fault can not be separated.
- If the temperature process includes an odd number of open loop unstable poles, the deviations caused by the high-C_{A0} contradict with the deviations caused by T-sensor-bias-high so the high-C_{A0} can be removed.

Fault 3: F-sensor-bias-low. Similar to an L-sensor-bias, this can cause both the level and the flow rate control systems to deviate. The interaction between these two control systems is of Type A, but they have opposite effects so that L-sensor-bias and F-sensor-bias can be separated either by Table 8 or by applying the alternative fault isolation method in Section 5

Fault 4: FJ-sensor-bias-low. FJ sensor is located in the inner loop of the temperature cascade control system. According to the previous cause-effect knowledge, if only outer loop controller deviates, inner loop sensor bias is the fault and the sensor bias has the same direction as the deviation of that sensor measurement.

Fault 5: LV-valve-bias-high. A valve bias only causes its own control system to deviate. The fault candidate from Figure 22 is {LV-valve-bias-high, an unknown disturbance of L}. If Figure 23 is available, the unknown disturbance can be replaced with low F_{1MAX}.

Fault 6: FV-valve-bias-high. Similar to Fault 5; the fault candidate from Figure 22 is {FV-valve-bias-high, an unknown disturbance of F} and from Figure 23, the unknown disturbance can be replaced with high F_{MAX}.

Fault 7: FJV-valve-bias-low. FJV valve is located in the inner loop of the temperature cascade control system. If only the inner loop controller deviates then the fault relates to the inner loop. The fault candidate set is {FJV-valve-bias, an unknown disturbance of FJ}. If Figure 23 is known, the unknown disturbance can be replaced with FJ_{MAX}. Fault directions can be inferred as {FJV-valve-bias-low, low-FJ_{MAX}} by the inner controller deviation.

Faults 8 to 10: low-F_{1MAX}, low-FJ_{MAX}, low-F_{MAX}. Similar to Fault 5 to Fault 7, these three faults cannot be separated from the related valve bias.

Fault 11: low-F_0. If F_0 is low, both the level and the temperature control systems deviate. C_A deviates as well. From Figure 22 it can be seen a common disturbance of L, T and C_A must be the cause of these effects. If Figure 23 is known, F_0 can then be isolated because the flow rate control system doesn't deviate and F_0 is the only common ancestor of level and temperature control systems. The direction of F_0 can be determined from either the deviation in the level or the temperature controller outputs.

Fault 12: low-K_0. Both the outer and the inner loop controllers of the temperature control system will deviate, as will C_A. Based on the control loop deviations and Figure 22, initially the fault candidate set is {T-sensor-bias-high, high-C_A, an unknown common disturbance of T and C_A}. If Figure 23 is known, the common disturbance can then be replaced with K or K_0, and the high-C_A can be replaced with high-C_{A0}. Flow rate F_0 is not included in the fault candidate set because it is the ancestor of L that doesn't deviate. Further separation depends on the stability of the open loop process:

- if the temperature process is open loop stable or has an even number of open loop unstable poles, the controller deviations caused by the high-C_{A0} and T-sensor-bias-high contradict leaving low K_0;
- if the temperature process has an odd number of open loop unstable poles, the controller deviations caused by high C_{A0} contradict, so the fault candidate shrinks to {low-K_0, T-sensor-bias-high}.

Fault 13: high-C_{A0}. Concentration C_A will be high and both the outer and the inner loop controllers of the temperature control system will deviate. The same arguments hold as for Fault 12 so the candidate set shrinks to be {high-C_{A0}, low-K_0, T-sensor-bias-high}. Again further separation depends on the stability of the open loop process:

- if the temperature process is open loop stable or has an even number of open loop unstable poles, the three elements cannot be separated;
- if the temperature process has an odd number of open loop unstable poles, the controller deviations caused by T-sensor-bias-high contradict, so the fault candidate shrinks to {low-K_0, high-C_{A0}}.

Fault 14: low-U_0. Both controllers in the temperature cascade control system deviate. Because the other two control systems and C_A don't deviate, from Figure 22, the fault must be from, an unknown disturbance of T. If Figure 23 is known, the unknown disturbance can be replaced with T_0, U_0, TJ_0. However these three disturbances can not be separated if there is no further information.

7. CONCLUSIONS

A self-validating control system (SEVACS) based approach to plant fault detection and diagnosis has been proposed that enables the distribution of these tasks throughout a plant. The approach itself is targeted on control systems that inherently eliminate steady state error; it is modular, steady state based, requires very little process specific information and should therefore be attractive to control system's implementers who seek economies of scale. Considerable effort has been expended to ensure that the approach is applicable to virtually all types of linear or weakly non-linear plant, whether they are open loop stable or not, have a type number of zero or not and so on.

The approach is founded on the application of control systems theory to single and cascade control systems with integral action. This results in the derivation of cause-effect knowledge and fault isolation procedures that take into account factors like interactions between control systems, and the availability of non-control-loop-based sensors. Cause-effect knowledge can be represented by a number of tables. Two fault isolation procedures are needed, the more efficient should be suitable for most processes with the exception of those with type numbers greater than zero. Blatantly obvious faults like sticking valves are not accommodated, but these can easily be detected and isolated using a simple rule-base, which can also be distributed to the FDD modules.

The approach has been tested on a simulated CSTR successfully; 14 faults have been examined in all. All faults have been identified and most of them have been isolated. The approach is thought to be superior to traditional SDG-based fault diagnosis methods because of its ease of implementation. As such, it is very attractive.

Although beyond the scope of this paper, its applicability has been demonstrated on the 24-loop Kodak Eastman benchmark (Chen & Howell, 2000).

As for the approach's general applicability, clearly considerable effort would be required to examine the many different situations that exist on real plants. A disturbance can result from internal or external influences, such as material contamination, mechanical failure or mal-operation. Changes in operating point and throughput can also be viewed as disturbances. The extent to which these might be diagnosed would depend on the extent to which they affect the steady state and on the knowledge that is available to facilitate their isolation. For instance, the approach would not be able to detect the presence of a sensor bias if it existed at the time the plant was started up. Although weakly non-linear processes have been examined in some detail, the paper has avoided to mention strongly non-linear processes. This is partly because the concept of steady state might now be different (e.g. as a result of limit cycle oscillations) and partly because the authors haven't looked at this area because it would be such a major task. Similarly the dynamic situation has been avoided. For instance the extent to which the approach can be modified to accommodate plants, which are required to slowly track or have over-ride control schemes, has not been examined. Our suspicions are that the difficulty, once again, would be more to do with the existence and identification of some form of quasi-steady state, than to revising the approach to accommodate these 'special cases'.

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